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JEL: G11, G12, G13, G17
Expected Correlation and Future Market Returns

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Implied correlation, jointly extracted from index and stock options, is a robust predictor of long-term market returns. We document that its predictive power stems from its role as a leading procyclical state variable, predicting future investment opportunities, that is, financial-market risks and macroeconomic conditions, for up to 18 months ahead. The predictability is inherited from the interplay between its three main components—implied market variance, implied idiosyncratic variance, and the implied dispersion of market betas—and not subsumed by measures of tail risk. We also provide first empirical evidence of out-of-sample predictability, leading to substantial economic gains for market-timing strategies.

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Option prices, by construction, reflect investors’ expectations about future price movements. Hence, measures of risk extracted from option markets are natural candidates for predicting future (aggregate) stock returns. In particular, one of the most robust option-implied predictors of long-term market excess returns is implied correlation, that is, the average expected correlation between individual stocks jointly extracted from the cross-section of individual stock options and index options (see, e.g., Driessen, Maenhout, and Vilkov (2005, 2012), Cosemans (2011), and Faria, Kosowski, and Wang (2016)). However, although this predictability is often linked to downside (“tail”) risk or, more generally, economic uncertainty, its exact underlying economic rationale is not yet well understood.

Consequently, the main objective of this paper is to study the economics behind the predictive power of implied correlation and the channels through which it is related to future investment opportunities. Our main findings can be summarized as follows. The market return predictability of option-implied correlation stems from its role as a leading procyclical state variable, a role that differentiates it from variables like the VIX volatility index and the variance risk premium, which are typically considered fear and tail risk proxies. In particular, option-implied correlation forecasts future financial risks as well as future economic growth, economic activity, and (economic) uncertainty at long horizons. It inherits its predictive power from its three key determinants—aggregate risk, idiosyncratic risk, and the cross-sectional dispersion of systematic risk—which, in combination, predict future financial and macroeconomic risks as well as future market returns even better. Finally, we demonstrate that implied correlation also predicts market excess returns out-of-sample, again for up to 12-month horizons. We now discuss these findings in more detail.

In a first step, we use a stylized conceptual framework to illustrate how the average expected correlation depends on its three main determinants—aggregate risk, idiosyncratic risk, and the cross-sectional dispersion of systematic risk—and demonstrate how these variables can...

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1Market return predictability using index-based option-implied variables is documented in Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), and Bollerslev, Marrone, Xu, and Zhou (2014) for the variance risk premium, as well as in Feunou, Jahan-Parvar, and Okou (2017) and Kilic and Shaliastovich (2017) for the downside semivariance risk premium. Moreover, long-term market return predictability by past realized correlation is discussed in Pollet and Wilson (2010).
be constructed from options data. Consistent with our framework, we find that, empirically, variations in implied market variance and implied idiosyncratic variance can explain more than 60% (and up to 80%) of monthly variations in implied correlation. Intuitively, an increase in implied market variance implies a stronger comovement among individual stocks, because the increase strengthens the importance of aggregate shocks. Conversely, when implied idiosyncratic variance increases, implied correlation declines, because stock-specific shocks are, to a larger extent, responsible for fluctuations in individual stock returns.

Second, we study how implied correlation and its components are related to future financial risk and macro-economic conditions. We find that these variables act as state variables, predicting different elements of the future investment opportunity set. In particular, implied correlation significantly predicts future realized correlation for long horizons. It inherits its predictive power from its three main components, which are strong predictors of their realized counterparts, though some of the components’ predictive power is lost through aggregation (i.e., linear combinations of the option-implied components typically outperform implied correlation). On the macro-economic side, implied correlation acts as a leading procyclical state variable. It positively forecasts economic growth in the form of reduced unemployment and a stronger leading indicator (which captures the long-term growth rate in the coincident economic activity). Also, it is negatively related to future economic uncertainty and a contrarian sentiment index, and positively related to future market valuations. Again, most of this predictive power is inherited from its components, and linear combinations of the latter often demonstrate a superior predictive performance (i.e., provide additional information).

Next, we present a variety of direct and indirect tests for market return predictability by implied correlation. In-sample, we confirm the findings in the literature that implied correlation significantly predicts future market excess returns for up to 1-year horizons, always with a positive coefficient and the highest predictive power in univariate regressions. Importantly, its predictive power is robust to controlling for other option-based variables built from the

\[ \text{The existing literature has linked each of these variables—under the actual probability measure—to stock returns. For example, Guo and Savickas (2006) show that idiosyncratic volatility predicts future market returns, and Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) rely on the factor structure of idiosyncratic risk to explain the cross-section of stock returns. Santos and Veronesi (2004) and Boloorforoosh, Christoffersen, Fournier, and Gourieroux (2017) relate the dispersion of market betas to the equity risk premium.} \]
marginal distribution of market returns, such as the risk premiums for market variance (e.g., Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011)) and downside semivariance (e.g., Kilic and Shaliastovich (2017), Feunou, Jahan-Parvar, and Okou (2017)), both of which are usually considered proxies for tail risk. Two of the option-implied components (idiosyncratic variance and the dispersion of market betas) also predict future returns, though with lower $R^2$s. Consistent with our findings for risk predictability discussed above, linear combinations of its components perform even better.

Using a vector autoregression (VAR) model similar to the one of Campbell (1991), we then analyze the joint dynamics, in particular the shock propagation, of implied correlation, its components, the market excess return, and dividend growth. Consistent with economic intuition, we find that past dividend growth negatively affects implied correlation; that is, implied correlation increases in adverse economic conditions. Decomposing implied correlation into components again proves useful in improving the model’s fit. Finally, we document that, consistent with the intuition from the present-value relation (see, e.g., Campbell and Shiller (1988) and Campbell (1991)), revisions in expected market excess returns, as predicted by implied correlation, are negatively correlated with contemporaneous market excess returns.

Lastly, we provide a novel analysis of out-of-sample return predictability by implied correlation. Using traditional regression techniques, we document a significant predictive power of implied correlation for horizons of up to 6 months. However, we also find that traditional out-of-sample regression techniques cannot fully exploit the predictive power of many option-implied predictors, because they require long historical estimation windows, whereas the sample period of option-implied variables is rather limited. For example, for an estimation window shorter than 5 years, only implied correlation and its risk premium show any predictive power, whereas for a long estimation window of 10 years, also idiosyncratic variance and the risk premiums for variance and downside semivariance deliver some predictability, though significance is difficult to establish. In lieu of this evidence, we propose a novel out-of-sample predictability method that extends the contemporaneous-beta approach (see, e.g., Cutler, Poterba, and Summers (1989), Roll (1988)). Our method combines high-frequency increments in option-implied variables with
the variables’ forward-looking risk premiums to predict future market excess returns.\footnote{Pyun (2019) proposes a similar methodology, which relies on shocks to high-frequency realized variance to estimate the variance-risk-premium beta. Instead, we suggest using increments in option-implied variables.} For predictions based on correlation and downside semivariance risk, our approach leads to out-of-sample $R^2$'s of around 8\% for a 1-month horizon, 6\% to 7.5\% for 3- to 6-month horizons, and of about 2.5\% for 12-month horizons. Consistent with our initial motivation, we link the better performance of our new approach to its stable (robust to outliers) and up-to-date regression coefficients. These results imply strong economic gains; for example, using the return predictions by correlation risk in a market-timing strategy significantly improves investors’ risk-adjusted returns for horizons up to 1 year.

Our work is related to several strands of the literature, for example, the literature on market return predictability using information extracted from option markets.\footnote{For an extensive literature survey, confer with Christoffersen, Jacobs, and Chang (2013). Goyal and Welch (2008) carefully analyze and discuss market return predictability more generally.} Driessen, Maenhout, and Vilkov (2005, 2012), Cosemans (2011), and Faria, Kosowski, and Wang (2016) discuss the in-sample market return predictability of correlation-related variables. Our key contribution to this literature is that we carefully analyze the economic rationale behind the predictability of implied correlation, tracing it back to the predictive power of its main determinants for future financial and macroeconomic risks.\footnote{We rely on techniques introduced in Buss and Vilkov (2012) to construct novel estimates of aggregate idiosyncratic risk and the cross-sectional dispersion of market betas from options data.} Also, unlike these papers, we study out-of-sample return predictability. For that purpose, we provide a novel extension to the contemporaneous-beta approach that improves out-of-sample return forecasts for option-implied variables.

Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), and Bollerslev, Marrone, Xu, and Zhou (2014) show that the variance risk premium robustly predicts market returns for horizons of up to one quarter. Longer-term predictability by various components of the variance risk premium is presented in Fan, Xiao, and Zhou (2018), who rely on a decomposition into a premium for variance risk and one for higher-order risks; Feunou, Jahan-Parvar, and Okou (2017) and Kilic and Shaliastovich (2017), who use decompositions into upside (good) and downside (bad) semivariance risk premiums; and Bollerslev, Todorov, and Xu (2015), who focus on jump components. These papers exclusively focus on information extracted from the marginal distribution of the market, whereas we highlight the importance of information extracted from
the joint distribution of the market and individual stocks. In particular, we carefully document that the predictability of implied correlation is not redundant relative to purely index-based components. Finally, our work is related to Martin and Wagner (Forthcoming), who document return predictability for individual stock returns using a combination of expected market variance and a stock’s expected (“excess”) variance, both of which are extracted from option prices. We operate with a similar concept but on the aggregate level.


Our contribution to this literature is to empirically link variations in implied correlation and its components to variations in future financial market and macro-economic conditions by highlighting the role of implied correlation as a leading procyclical state variable.

Our analysis also relates to the literature on idiosyncratic risk. Ang, Hodrick, Xing, and Zhang (2006, 2009) document a negative relation between idiosyncratic risk and stock returns in the cross-section. Schneider, Wagner, and Zechnner (2017) relate the pricing of idiosyncratic risk to (implied) skewness. Goyal and Santa-Clara (2003) document that average variance (their proxy for idiosyncratic risk) positively predicts future market returns, whereas Bali, Cakici, Yan, and Zhang (2005) cannot find a significant relation between idiosyncratic volatility and future market returns. Guo and Savickas (2006) show that, when combined with aggregate stock market volatility, the value-weighted idiosyncratic volatility is significantly negatively related to future market returns. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) rely on the factor structure of idiosyncratic volatility to explore the cross-section of stock returns. We contribute
to this literature by linking the predictive power of the implied correlation to idiosyncratic risk. In particular, because implied correlation positively predicts future market returns but is negatively related to idiosyncratic volatility, our evidence is consistent with a negative price for idiosyncratic risk.

Consistent with our conceptual framework for expected correlation and our empirical findings, Kogan and Papanikolaou (2012, 2013) demonstrate that idiosyncratic volatility and the dispersion of market betas are positively related to growth opportunities, which, in turn, are negatively related to the equity risk premium. Similarly, in the model of Santos and Veronesi (2004), the equity risk premium is low when the dispersion of systematic risk is high, and, in the model of Boloorforoosh, Christoffersen, Fournier, and Gourieroux (2017), market betas positively (negatively) covary with the pricing kernel for low (high) beta values, so that dispersion of the market betas goes down (up) in bad (good) economic conditions.

The rest of this paper is organized as follows: Section 1 proposes a conceptual framework to identify the main determinants of average expected correlation and shows how to construct these components from options data. Section 2 explores the role of implied correlation as a state variable, linking it and its components to future financial and economic conditions. Section 3 documents the in-sample predictive power of implied correlation and its components. Section 4 discusses out-of-sample predictability and introduces a novel forecasting approach based on contemporaneous betas. Section 5 provides robustness tests. Section 6 concludes.

1 Expected Correlation and Its Determinants

In this section, we discuss the relation between correlation and its main components. For that purpose, we introduce a stylized framework that connects expected correlation to aggregate risk, idiosyncratic risk, and the dispersion of systematic betas. We then show how these variables can be constructed from options data and empirically explore their relation.
1.1 Theoretical Framework

Our conceptual framework is based on that of Kelly, Lustig, and Van Nieuwerburgh (2016) and relies on a discrete-time, composite one-factor structure for stock returns. In particular, we consider a broad index consisting of a large number of stocks, denoted by \( i \in \{1, \ldots, N\} \). The annual log-return of each individual stock, \( r_{i,t+1} \), is described by the following dynamics:

\[
r_{i,t+1} = \mu_{i,t} + \beta_{i,t} \varepsilon_{A,t+1} + \varepsilon_{i,Id,t+1},
\]

(1)

where \( \varepsilon_{A,t+1} \) denotes an aggregate shock common to all stocks, and \( \varepsilon_{i,Id,t+1} \) denotes an idiosyncratic (stock-specific) shock, which is independent of the aggregate shock and of the idiosyncratic shocks of the other stocks. Both aggregate and idiosyncratic shocks might comprise several components, such as Gaussian shocks, jumps, or separate up and down jumps.\(^6\) Importantly, the specific distribution of the aggregate and the idiosyncratic shocks is not important for our analysis; what is relevant is the total expected variance of each factor, denoted by \( \sigma^2_{A,t} \equiv \text{Var}(\varepsilon_{A,t+1}) \) and \( \sigma^2_{i,Id,t} \equiv \text{Var}(\varepsilon_{i,Id,t+1}) \). The exposure of the individual stocks to aggregate shocks (“market betas”), \( \beta_{i,t} \), is assumed to be stochastic and distributed around the natural mean of 1.0 with time-varying variance \( \sigma^2_{\beta,t} \).

The total expected return variance of stock \( i \), \( \sigma^2_{i,t} \equiv \text{Var}(r_{i,t+1}) \), is equal to

\[
\sigma^2_{i,t} = \beta_{i,t}^2 \sigma^2_{A,t} + \sigma^2_{i,Id,t},
\]

(2)

and its expected return is \( \mu_{i,t} \), which is the sum of the expected return on the index and risk adjustments. The return on the index is given by \( r_{t+1} \equiv \sum_{i=1}^{N} \omega_{i,t} r_{i,t+1} \), where \( \omega_{i,t} \) denotes the index weight of stock \( i \).\(^7\) As the number of stocks becomes large (i.e., \( N \to \infty \)), the idiosyncratic shocks are diversified. Because the weighted average of the market betas is 1.0, this implies that the conditional expected variance of the index is equal to \( \sigma^2_{A,t} \). As it follows from

\(^6\)For instance, a Merton jump setting similar to that used by Kelly, Lustig, and Van Nieuwerburgh (2016) can be captured by decomposing the aggregate shock into a systematic Gaussian shock \( \varepsilon_{A,t+1} \) and a systematic jump \( J_{A,t+1} \) and by decomposing the idiosyncratic shock into an idiosyncratic Gaussian shock \( \varepsilon_{i,Id,t+1} \) and an idiosyncratic jump \( J_{i,Id,t+1} \). The stock return dynamics then would become

\[
r_{i,t+1} = \mu_{i,t} + \beta_{i,t} \varepsilon_{A,t+1} + \beta_{i,t} J_{A,t+1} + \varepsilon_{i,Id,t+1} + J_{i,Id,t+1}.
\]

Intuitively, the exposure with respect to the aggregate jump, \( \beta_{i,t} \), captures the stronger reaction of high beta stocks to systematic jumps and is equivalent to “scaling” the mean and the volatility of their jump size distributions.

\(^7\)For ease of exposition, we ignore non-linearities and volatility adjustments.
expression (2), the cross-sectional average expected stock variance is given by \((1+\sigma_{\beta,t}^2)\sigma_{A,t}^2 + \sigma_{i,t}^2\) and, naturally, is an increasing function of the aggregate variance, idiosyncratic variance, and the cross-sectional dispersion of systematic betas.

For the identification of the average correlation among stocks, note that index variance can be computed in two ways: (1) directly from the index and (2) indirectly through the portfolio of its constituents. Formally, this computation yields the restriction that the time-\(t\) expected variance of the index, \(\sigma_{A,t}^2\), must be equal to the expected variance of the portfolio of its constituents:

\[
\sigma_{A,t}^2 \triangleq \sum_{i=1}^{N} \sum_{i' = 1}^{N} \omega_{i,t} \omega_{i',t} \sigma_{i,t} \sigma_{i',t} \rho_{i,i',t}, \tag{3}
\]

where \(\rho_{i,i',t}\) denotes the correlation between the returns of stocks \(i\) and \(i'\). Under the assumption of equal pairwise correlations \((\rho_{i,i',t} = \rho_{j,j',t}, \forall i, i', j, j')\), the "equicorrelation" is given by\(^8\)

\[
\text{Corr}_t = \frac{\sigma_{A,t}^2 - \sum_{i=1}^{N} \omega_{i,t}^2 \sigma_{i,t}^2}{\sum_{i=1}^{N} \sum_{i' \neq i} \omega_{i,t} \omega_{i',t} \sigma_{i,t} \sigma_{i',t}}. \tag{4}
\]

In the case of a large number of stocks (i.e., \(N \to \infty\)), this correlation can be approximated as

\[
\text{Corr}_t \approx \frac{\sigma_{A,t}^2}{\bar{\sigma}_i \bar{\sigma}_{i'}}, \tag{5}
\]

where \(\bar{\sigma}_i \bar{\sigma}_{i'}\) denotes the average product of individual variances.

Because of its non-linearity, deriving a more precise functional form of this correlation without additional simplifying assumptions is not possible. However, simple simulations show that the average correlation is an increasing function of the systematic variance (which enters both numerator and denominator) and a decreasing function of the idiosyncratic variance and of the dispersion of systematic betas.\(^9\)

\(^8\)Elton and Gruber (1973) are one of the first to use this average correlation under the physical measure. Driessen, Maenhout, and Vilkov (2005) and Skinzi and Refenes (2005) introduced it under the risk-neutral measure, with the later literature referring to it as equicorrelation.

\(^9\)We abstract from variations in index weights, which, over short periods of time, do not contribute much to fluctuations in expected correlation. Under the risk-neutral probability measure, risk premiums could also potentially matter, for example, in the case of jumps, by altering the likelihood of jumps and the jump size distribution.
1.2 Variables Construction

Note that while computing implied correlation and its component under the physical probability measure (P-measure) is relatively straightforward, our main interest is in their counterparts under the risk-neutral probability measure (Q-measure). For this purpose, we rely on data from the S&P 500 for a sample period from January 1996 to December 2017. We use daily data on index and individual stock options from the Surface File of Ivy DB OptionMetrics and data on the daily realized returns from CRSP. For the S&P 500, we also obtain intraday returns from TickData. Data on the S&P 500 index composition and the stocks’ index weights (i.e., relative market capitalizations) are obtained from Compustat and CRSP.

In a first step, we compute option-implied variances (i.e., the expected variance under the risk-neutral measure) for all stocks and the index. In particular, we use simple variance swaps, as introduced by Martin (2013, 2017), to construct the day-t implied variance for options with maturity T, \( IV(t,T) \). Based on the implied variances of the index and the individual stocks, we then compute implied correlation, \( IC(t,T) \), using expression (4). Note that constructing the option-implied idiosyncratic variance (IdIV) and the option-implied dispersion of market (systematic) betas (IDMB) requires option-implied market betas, \( \beta^Q(t,T) \). For that purpose, we rely on the technique introduced by Buss and Vilkov (2012), who show how one can construct a heterogeneous option-implied correlation matrix for all components of an index. Their approach relies on a parametric form that relates implied correlations to the physical correlation under the P-measure and a heterogeneous correlation risk premium. As Buss and Vilkov show, the market betas computed from this implied variance-covariance matrix predict future realized betas significantly better than traditional rolling-window betas. The option-implied dispersion

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10 We select options with 1 to 12 months to maturity and an (absolute) delta of less than or equal to 0.5. On average, options data are available for 491 of the 500 index constituents.
11 We merge the two datasets through the CCM Linking Table using GVKEY and IID to link to PERMNO. Matching to options data is implemented through the historical CUSIP link, provided by OptionMetrics.
12 Computing expected variances using log contracts, that is, model-free implied variances, like in Dumas (1995), Britten-Jones and Neuberger (2000), and Bakshi, Kapadia, and Madan (2003), does not affect our results. These results are available on request.
13 Appendix A discusses the details of this approach. Implied correlation, \( IC(t,T) \), also can be constructed as the average correlation from the resultant heterogeneous correlation matrix. However, this average and the equicorrelation computed from (4) are almost perfectly correlated (ranging from 0.97 to 0.99), and the predictability results are the same. Hence, for ease of exposition, we only report the results for option-implied equicorrelation in the following.
The table reports summary statistics for implied correlation (IC), implied dispersion of market betas (IDMB), implied idiosyncratic variance (IdIV), and implied market variance (IV). Statistics are reported for maturities of 1 to 12 months over a sample period from January 1996 to December 2017 and, where applicable, in annual terms.

The average implied correlation is about 0.38. It is increasing with maturity and is highly persistent (with a first-order autocorrelation AC(1) of 0.77) but still considerably varies over time, with fluctuations being almost symmetric around the mean. The annualized S&P 500 implied index variance is 0.042% (which translates into an implied volatility of 20.5%). Also, it is highly persistent (with a first-order autocorrelation of 0.81); it substantially fluctuates over time; and it has a generally positive skewness. The implied idiosyncratic variance is extremely persistent (with AC(1) of 0.93), decreasing with maturity, and is slightly positively skewed. The dispersion of market betas is positively skewed, decreasing with maturity, and is slightly less persistent than the correlation, with a monthly autocorrelation of 0.55.

### 1.3 Dynamics of Implied Correlation and Its Components

Figure 1 depicts the dynamics of implied correlation and its components over time for a 1-month maturity. Implied correlation, being a bounded variable, displays (relatively) smaller fluctuations than do the implied variances. Also, the most pronounced moves in implied correlation do not
necessarily coincide with those in the implied variances. Consistent with this, the time-series correlations between the implied correlation and the implied variances (which behave in a similar way most of the time) are not that high; for example, the correlation with implied market variance is 0.58 in levels (or 0.64 in differences); the correlation with idiosyncratic variance is −0.16 in levels (−0.18 in differences). Finally, the dispersion of market betas is quite volatile.

To evaluate empirically how the different components affect implied correlation, we rely on simple regressions of monthly changes in implied correlation on changes in its components. To highlight the incremental power of each of the components, we first identify the most important variable; then the most important pair of variables; and, finally, include all three explanatory variables (“hierarchical regression”). Table 2 provides results for all available maturities.\footnote{We have carried out the same exercise for realized correlation and its components. Table A2 in Appendix D provide results, which are comparable. In addition to using monthly increments in regressions, we also used log differences. Doing so leads to comparable results, with slightly worse explanatory power.}
Table 2: Determinants of implied correlation. The table reports the results for regressions of monthly changes in implied correlation on respective monthly changes in its components, namely, the dispersion of market betas (IDMB), idiosyncratic variance (IdIV), and market variance (IV). For each maturity, we report the specifications with one, two, and three independent variables with the highest $R^2$. The data are sampled monthly from January 1996 to December 2017. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively; based on Newey and West (1987) standard errors.

As shown in Table 2, implied market variance captures the largest fraction of variations in implied correlation, with $R^2$s between 40% and 55% across the different horizons. Implied idiosyncratic variance is the second most important component, adding around 20%–25% of $R^2$. The implied dispersion of market betas is less important and typically explains only additional 1%–2% of the variations in implied correlation and is insignificant for horizons of 6 months and longer. Consistent with our stylized framework, implied market and idiosyncratic variance affect implied correlation with opposite signs.

2 Implied Correlation and Future Investment Opportunities

In this section, we analyze the potential role of implied correlation and its components as state variables describing future investment opportunities. First, we concentrate on variables capturing future financial risks, and, second, we study variables capturing future economic conditions.

2.1 Implied Correlation and Future Financial Risks

Future aggregate and idiosyncratic variances as well as the future correlations among individual stocks are key elements of the future investment opportunity set of investors. Hence, in a first step, we now analyze the predictive power of implied correlation and its components for these financial variables. For that purpose, we rely on a series of predictive regressions of future
Figure 2: Financial risk predictions: Predictive power. The figure reports the $R^2$ of predictive regressions of future realized financial risk measures on current option-implied variables for horizons of 1 to 12 months. Panels A to D report the $R^2$ for realized correlation, realized market variance, realized idiosyncratic variance, and the realized dispersion of market betas, respectively. Results are based on monthly-sampled data from January 1996 to December 2017.

realized risk measures (correlation, market variance, idiosyncratic variance, and dispersion of market betas) on the respective date-$t$ option-implied variables (with matching maturity).\textsuperscript{16}

The predictive power of these regressions (in terms of $R^2$) is illustrated in Figure 2 across various horizons. For all horizons, implied correlation is the best predictor of future realized correlation, outperforming even the linear combination of its components (which affect future realized correlation in a way that one would expect). In univariate regressions, realized market variance is best predicted by implied market variance (Panel B), whereas both idiosyncratic variance and the dispersion of market betas are best predicted by implied idiosyncratic variance

\textsuperscript{16}Realized variance is computed as the sum of squared returns; using demeaned daily returns for individual stocks and 5-minute intraday returns for the S&P 500 (as suggested by Liu, Patton, and Sheppard 2015). Consistent with our construction of implied correlation, we compute realized correlation using expression (4), now based on realized variances instead of implied ones. The corresponding realized idiosyncratic variance and the dispersion of market betas are computed from market model regressions for each stock.
Table 3: Financial risk predictions. The table reports the results for selected specifications of predictive regressions of future realized financial risk measures (correlation, market variance, idiosyncratic variance, and the dispersion of market betas) on current option-implied variables for horizons of 1 to 12 months. The estimation results are based on monthly-sampled data from January 1996 to December 2017. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively; based on Newey and West (1987) standard errors. (Panels C and D). Also, for all these variables, the linear combination of the components is usually superior to any single predictor.

Table 3 contains the corresponding regression coefficients. Notably, some components have signs opposite to those one would expect from their relation to implied correlation and the relation between implied correlation and future financial risks. For example, whereas the regression coefficient of implied correlation for future idiosyncratic variance is negative and the correlation between implied correlation and implied market variance is positive, the regression coefficient of implied market variance for future idiosyncratic variance is actually positive. This indicates that, on occasions, implied correlation and its main components convey different information about future investment opportunities.
### 2.2 Implied Correlation and Future Economic Conditions

Naturally, future investment opportunities are also driven by the underlying economic conditions. Hence, in a second step, we now study the predictive power of implied correlation for future economic fundamentals by regressing future (log)changes in macro-economic variables on the date-$t$-implied variables.

For the macro-economic variables, we focus on variables that have been shown to be linked to the state of the economy and are observed at a monthly frequency. These include (1) the Industrial Production Index (INDPRO), a measure of the real output of all facilities in the United States; (2) the Civilian Unemployment Rate (UNRATE); (3) the Coincident Economic Activity Index (CEA), an aggregate measure of economic activity; (4) the Leading Index (LI), which aims to predict the 6-month growth rate in CEA; (4) the TED spread (TED), capturing the difference between interbank rates and short-term government yields;\(^{17}\) (5) the price-dividend ratio on the broad CRSP index (PD), a measure of market valuations; (6) an indicator of investor sentiment (SENT) following Baker and Wurgler (2007); and (7) the Baseline Overall Index (BOI), an indicator of economic policy uncertainty by Baker, Bloom, and Davis (2016).\(^{18}\)

Figure 3 illustrates the predictive power (in terms of \(R^2\)) of the option-implied variables across various horizons. Table 4 contains the corresponding regression coefficients. At horizons of 6 months or longer, implied correlation significantly predicts many of the macro-economic variables, with the exception of industrial production (INDPRO), the TED spread, and coincident economic activity (CEA). In particular, being positively related to the leading indicator (LI) and negatively related to unemployment (UNRATE), economic uncertainty (BOI), and sentiment (SENT), high implied correlation predicts long-term improvements in economic fundamentals.\(^{19}\) Moreover, it predicts higher market valuation (i.e., a higher price-dividend ratio). Hence, overall, the empirical evidence indicates that implied correlation is a leading procyclical state variable that predicts economic growth for 6 to 18 months ahead.

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\(^{17}\)These variables are all obtained from the Federal Reserve Bank of St. Louis.

\(^{18}\)We appreciate having an opportunity to download updated series of the Investor Sentiment index from the website of Jeffrey Wurgler (http://people.stern.nyu.edu/jwurgler/) and that of the Economic Policy Uncertainty index from the website of the authors (www.policyuncertainty.com/).

\(^{19}\)Note that sentiment (SENT) is a contrarian predictor; that is, when sentiment is high, future returns are low and vice versa (see, e.g., Baker, Wurgler, and Yuan 2012).
Figure 3: Economic condition predictions: Predictive power. The figure reports the $R^2$ of predictive regressions of future (log)changes in macro-economic variables on current option-implied variables for horizons of 1 to 12 months. Results are based on monthly-sampled data from January 1996 to December 2018.
Table 4: Economic condition predictions. The table reports the results for predictive regressions of future (log)changes in macro-economic variables on current option-implied variables for 1- to 12-month horizons. Estimation results are based on monthly-sampled data from January 1996 to December 2017. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively; based on Newey and West (1987) standard errors.
Individually, implied market variance and the implied dispersion of market betas (for horizons of less than 3 months) are significant predictors of industrial production (INDPRO) and the coincident economic activity (CEA). Also, the implied idiosyncratic variance predicts financial market valuations (especially over the long term). Notably, however, linear combinations of the three correlation components almost always outperform implied correlation (in fact, any single predictor) and, in most cases, do so substantially. This result indicates that implied correlation actually inherits its predictability from its three components and that (a large fraction of the available) information is lost during aggregation. For example, in the case of the coincident economic activity indicator (CEA), the joint regressions deliver high $R^2$s, and regression coefficients for implied market variance and the implied dispersion of market betas are usually significant. Yet implied correlation typically has a quite low predictive power and an insignificant coefficient for the coincident economic activity (CEA). Interestingly, the components of implied correlation can often predict future investment opportunity at different time horizons; for example, in predictions of industrial production implied idiosyncratic variance gains significance for long horizons, while implied market variance loses its significance.

3 Forecasting Market Returns

We now focus on the ability of implied correlation (and its components) to predict future market excess returns in-sample. We first discuss the empirical evidence from standard in-sample regressions, then present evidence from a VAR model, and, finally, study whether revisions in return forecasts are consistent with contemporaneous market excess returns.

3.1 Market Return Predictability

To study the in-sample predictability of market excess returns for various horizons, we rely on standard in-sample predictive regressions of the following form:

$$r_{t\rightarrow t+\tau_r} = \gamma + \sum_{k \leq K} \beta_k \text{PRED}_k(t, t + \tau_r) + \varepsilon_t,$$  \hspace{1cm} (7)
where \( r_{t \rightarrow t + \tau_r} \) denotes the market excess return from \( t \) to \( t + \tau_r \) and \( \text{PRED}_k(t, t + \tau_r) \) denotes a set of predictors (known at time \( t \)).\(^{20}\) We use market excess returns from the end of a month, and, when predicting returns for horizons longer than 1 month, we compute Newey and West (1987) standard errors to correct for autocorrelation due to overlapping observations.

To differentiate the predictability of implied correlation and its components from well-known proxies of downside risk, we expand the set of predictors to include risk premiums for correlation (CRP), variance (VRP), and upside and downside semivariances (\( VRP^u \) and \( VRP^d \)). In particular, the \textit{ex-ante} variance risk premium, \( VRP(t, T) \), is computed as the difference between the day-\( t \) implied variance from options with maturity \( T \) and the realized variance for the period from \( t - (T - t) + 1 \) to \( t \). Similarly, the correlation risk premium \( CRP(t, T) \) is computed \textit{ex-ante} using forward-looking implied and realized correlation from matching periods. The upside and downside semivariance risk premiums, \( VRP^u(t, T) \) and \( VRP^d(t, T) \), are computed as the difference between the risk-neutral expectations of upside and downside semivariances, \( IV^u(t, T) \) and \( IV^d(t, T) \) (following the corridor variance methodology of Andersen and Bondarenko 2007 and Andersen, Bondarenko, and Gonzalez-Perez 2015), and realized semivariances (constructed following Andersen, Bollerslev, Diebold, and Ebens 2001 and Feunou, Jahan-Parvar, and Okou 2017). Table A3 in Appendix D contains summary statistics for these variables, all of which are consistent with the findings in the literature.

Figure 4 reports the results for regression (7). Panel A shows that, in univariate regressions, implied correlation has the strongest predictive power (\( R^2 \)) for future market excess returns, except for the 1-month horizon. Its predictive power increases from about 3.5% at the 1-month horizon to around 25% for the 9- and 12-month horizons. Moreover, its regression coefficient is always highly significantly positive, with \( t \)-statistics consistently above 2 (Panel B). The components of implied correlation also perform quite well, especially the implied dispersion of market betas, which is highly significant and delivers \( R^2 \)’s of up to 17% for 6 and 9 months. Implied idiosyncratic variance is also significant, whereas implied market variance shows almost no predictability at any horizon. As shown in Panel A of Figure 4, the three components of implied correlation outperform implied correlation by a very large margin, boosting the \( R^2 \) by 15% (for

\(^{20}\)We always rely on variables extracted from options with a maturity matching the forecasting horizon.
Figure 4: In-sample return predictability. The figure depicts the results of the in-sample market excess return predictability regressions (7) for 1- to 12-month horizons. Panels A and B report the adjusted $R^2$ and $t$-statistics for regressions with implied correlation and/or its components as explanatory variables, respectively. Panels C and D report the adjusted $R^2$ and $t$-statistics for regressions with risk premiums for correlation ($CRP$), market variance ($VRP$), and upside and downside semivariances ($VRP_u$ and $VRP_d$) as explanatory variables, respectively. The sample period spans from January 1996 to December 2017, and the data are sampled monthly. Standard errors are corrected for autocorrelation following Newey and West (1987), and the black dotted lines represent 5% significance bounds.

A 1-year horizon) to almost 90% (for a 1-month horizon) in relative terms. The components are significant for most horizons, with consistent coefficient signs (Panel A of Table 5).

Panels C and D of Figure 4 illustrate that the predictive power of the risk premiums is typically weaker than that of implied correlation, though the downside semivariance risk premium delivers the highest $R^2$ at the shortest horizon of 1 month. Also, whereas the variance risk premium significantly predicts returns at short horizons, its predictive power and statistical significance quickly vanish as the horizon lengthens. Notably, the downside semivariance risk premium delivers a better predictability than the total variance risk premium, with $R^2$s of 7%–11% at short horizons and around 4% at longer horizons (consistent with the findings in
Table 5: In-sample return predictability. The table reports the results of the in-sample market excess return predictability regressions (7) for 1- to 12-month horizons. Panel A shows the results for univariate regressions with implied correlation \( (IC) \) or its three components as explanatory variables. Panel B shows the results for the same specifications with two additional controls: the correlation risk premium \( (CRP) \) and the downside semivariance risk premium \( (VRP_d) \). The sample period spans from January 1996 to December 2017, and the data are sampled monthly. \( ** \), \( * \), and \( * \) indicate significance at the 1%, 5%, and 10% level, respectively; based on Newey and West (1987) standard errors.

Feunou, Jahan-Parvar, and Okou (2017) and Kilic and Shaliastovich (2017)), with a regression coefficient that is always significantly positive.

Importantly, when jointly used with the risk premiums, implied correlation and its components always remain significant, with sign and significance mostly unchanged (Panel B of Table 5). In particular, although these regressors always improve the \( R^2 \) compared to the original specifications in Panel A, the correlation risk premium is actually never significant, and the downside semivariance risk premium counterintuitively changes sign and becomes insignificant for long horizons.

### 3.2 VAR Models

Studying the joint dynamics of the options-based variables and the market excess return can provide additional information on in-sample return predictability. In that regard, we follow Campbell (1991) and estimate a variety of VAR models of the following form:

\[
z_{t+1} = A z_t + \epsilon_{t+1},
\]
where $z_t$ denotes a $k$-dimensional vector consisting of the market excess return ($MKTRF$) and the “predictors.” Consistent with the literature, we always include the standard predictor—log dividend growth ($DIV$)—in addition to various combinations of options-based variables.

Table 6 summarizes the estimation results at a monthly frequency. As expected from the ability of the implied variables to predict future investment opportunities, most of these variables have significant predictive power in the market return equation of the VAR model. As a single add-on to dividend growth and the market excess return, implied correlation, the implied dispersion of market betas and implied idiosyncratic variance significantly predict expected returns, with $R^2$s of about 3%–4%. In contrast, implied market variance is not significant when used without other implied variables. When used jointly, the three correlation components outperform implied correlation, having an $R^2$ of 6.2%. Taking only the two variance components of implied correlation slightly decreases the explanatory power of the model (to 5.89%), but, again, the results are stronger than with implied correlation alone. The corresponding $R^2$s for longer horizons, depicted in Figure 5, confirm these conclusions.\(^{21}\) Quantitatively, the model featuring implied correlation delivers $R^2$s of up to 17.5% for 5 to 9 months and 14% for longer periods, but models including various correlation components deliver a substantially higher predictive power for most horizons with $R^2$s of up to 24%.

\(^{21}\)The long-term implied $R^2$s are computed by regressing realized returns on VAR-implied forecasts for market excess returns. $R^2$s are potentially biased at longer horizons because of autocorrelation in the predictive variables.
Figure 5: VAR-implied $R^2$ for market return forecasts. The figure shows the implied $R^2$ (expressed as a percentage) for predicting market excess returns based on various VAR(1) specifications of (8) for forecasting horizons of 1- to 12-month. All specifications include the market excess return and the log dividend growth rate for the CRSP aggregate index. The implied $R^2$ is based on regressing realized monthly market excess returns on VAR-implied return forecasts for a sample period from January 1996 to December 2017.

In contrast with the individual predictive regressions, the VAR model also allows us to understand how shocks to the various variables propagate through the system.\textsuperscript{22} Shocks to implied correlation positively affect market returns for up to 10 months (consistent with the results for the implied variance and implied idiosyncratic variance components). Shocks to market returns significantly (and negatively) affect implied idiosyncratic variance and the implied dispersion of market betas, while not significantly propagating to either implied market variance or implied correlation. Interestingly, implied correlation captures shocks to dividend growth with a negative sign, so that high current dividend growth leads to a lower implied correlation in the future. This negative link between dividend growth and implied correlation is generated by a positive link between dividend growth and implied idiosyncratic variance and the implied dispersion of market betas (to a lesser degree). Thus, a positive shock to today’s expected return, due to a positive dividend growth shock, lowers implied correlation by boosting the latter two, all leading to a lower expected return in the future.

\textsuperscript{22}For the sake of brevity, we omit the impulse response functions (IRFs) here; they are reported in Figures A1 and A2 in Appendix C for Models 1 and 5 of Table 6, respectively.
3.3 Return Forecasts and Contemporaneous Returns

Economic theory provides a tight link between revisions in expected market excess returns and contemporaneous market excess returns. In particular, using the Campbell and Shiller (1988) log-linearization, one can relate contemporaneous, unexpected excess returns, $e_{t+1} - E_t[e_{t+1}]$, to revisions in expected dividend growth rates and revisions in expected future excess returns:

$$e_{t+1} - E_t[e_{t+1}] = (E_{t+1} - E_t) \sum_n \rho^{n-1} \Delta d_{t+n} - (E_{t+1} - E_t) \sum_n \rho^n r_{f,t+1+n}$$

$$- (E_{t+1} - E_t) \sum_n \rho^n e_{t+1+n},$$

where $e_{t+1}$ denotes the time-$t$ excess return, $\Delta d_t$ denotes the log dividend-growth rate, $r_{f,t}$ denotes the time-$t$ risk-free rate, and $\rho$ denotes a parameter with a value slightly less than one.

All else equal, (9) implies that, because of the negative sign in front of the revisions to future expected excess returns, an increase in the forecasts of future market excess returns, $(E_{t+1} - E_t) e_{t+1+n}$, causes a lower contemporaneous excess return, $e_{t+1} - E_t[e_{t+1}]$. Consequently, to be consistent with economic theory, revisions in the forecasts of future market excess returns from (7) must negatively correlate with contemporaneous excess returns.

Empirically, we find that the correlation between increments in the predicted market excess returns and contemporaneous daily market excess returns is negative for most options-based variables. For example, the correlation between daily excess returns and changes in forecasts based on implied correlation is $-0.61$. For implied market variance and the implied dispersion of market betas, it is also negative, whereas it is positive ($0.17$) for implied idiosyncratic variance.\textsuperscript{23} For joint predictions based on all three components, the correlation with contemporaneous returns is also negative ($-0.41$). Hence, there is strong and robust empirical evidence that predictions based on the implied correlation are consistent with the relation stipulated by economic theory in the form of the present value relation.

\textsuperscript{23}For longer horizons, this correlation turns (modestly) negative.
4 Out-of-Sample Predictability

Although many variables have strong predictive power in-sample, hardly any evidence exists for out-of-sample predictability, as convincingly shown by Goyal and Welch (2008). Consequently, we now concentrate on the out-of-sample performance of implied correlation, its components, and various risk premiums.

4.1 Measuring Predictability

To evaluate the performance of a specific forecasting model $s$, we compare its predictive power to that of a model based on the historical mean of the market excess return ($s = 0$). This forecast serves as a natural benchmark, because, as documented by Goyal and Welch (2008) and Campbell and Thompson (2008), almost all predictive variables fail to beat it out-of-sample.

To measure the out-of-sample predictive power, we rely on two criterion. First, we consider the out-of-sample $R^2$ relative to the forecasts from the (benchmark) historical average return model:

$$R^2_{s,τ} = 1 - \frac{MSE_{s,τ}}{MSE_{0,τ}},$$

where $MSE_{s,τ} = \frac{1}{N} (e_{s,τ}^T \times e_{s,τ})$ denotes the mean-squared error of model $s$ computed from the $N \times 1$ vector of prediction errors $e_{s,τ}$ for horizon $τ$. A particular model, $s \geq 1$, outperforms the benchmark model based on the average historical return if the out-of-sample $R^2_{s,τ}$ is significantly positive.

Second, we assess a model’s predictive power by studying the certainty-equivalent gain of a mean-variance investor who follows a market-timing strategy based on the expected return signal (similar to the setting of Campbell and Thompson 2008). That is, we compute the gain

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24 Usually, out-of-sample performance is evaluated using a loss function that is either an economically meaningful criterion, such as utility or profits (e.g., Leitch and Tanner (1991), West, Edison, and Cho (1993), Della Corte, Sarno, and Tsiakas (2009)), or a statistical criterion (e.g., Diebold and Mariano (1995), McCracken (2007)). These approaches have been recently unified and extended by Giacomini and White (2006), who develop out-of-sample tests to compare the predictive ability of competing forecasts, given a general loss function under conditions of possibly misspecified models.

25 We also consider the Diebold and Mariano (1995) loss function, that is, the average squared-error loss relative to the predictions from the benchmark model: $δ_{s,τ} = MSE_{s,τ} - MSE_{0,τ}$. The inferences are unchanged relative to the out-of-sample $R^2$, with the results being available on request.
in certainty-equivalent return for a myopic mean-variance investor with a horizon of $\tau_r$ and risk aversion $\gamma = 1$, who uses the forecasts of model $s$ instead of the historical average return ($s = 0$). Formally, to compute the portfolio weight $w_{t,\tau,s} = \frac{\hat{r}_{s,t,\tau_r}}{\sigma^2}$ of the market portfolio, we use a model’s predicted excess return ($\hat{r}_{s,t,\tau_r}$) and the 1-year historical variance ($\sigma^2$). From the resultant time-series of realized returns $r_{s,\tau}$, one can then compute the mean-variance certainty equivalent $CE_{s,\tau_r}$ and the respective gain in the certainty equivalent return ($CE$ gain)

$$\Delta CE_{s,\tau_r} = CE_{s,\tau_r} - CE_{0,\tau_r}, \text{ where } CE_{s,\tau_r} = E[r_{s,\tau_r}^{MV}] - \frac{\gamma}{2}\sigma^2(r_{s,\tau_r}^{MV}).$$

Intuitively, this measures the economic benefit of a better performing portfolio resulting from a better market return forecast.

Because of the limited availability of options data, our sample period spans about 20 years. Consequently, asymptotic standard errors may not be accurate, so we resort to bootstrapping. Specifically, we use the moving-block bootstrap procedure of Künsch (1989) to randomly resample with replacement from the time series of a model’s forecasts to construct bootstrapped distributions for our performance measures. Using the bootstrapped distribution, we compute the $p$-value for the null hypothesis: $R^2 = 0$.

### 4.2 Traditional Out-of-Sample Approach

Traditionally, out-of-sample predictions are based on rolling-window estimations of the predictive regression (7) (with the addition of a time-specific intercept):

$$r_{t-\tau_r\rightarrow t} = \gamma_t + \sum_{k \in K} \beta_{k,t} PRED_k(t-\tau_r, t) + \varepsilon_t,$$

The estimated coefficients $\beta_{k,t}$, together with the time-$t$ value of the “predictors” $PRED_k(t, t+\tau_r)$ then form the out-of-sample return forecast, $r_{t-\tau_r\rightarrow t}$. Note that, at date $t$, one uses only observations from the past to avoid any look-ahead bias.

---

26. Following Campbell and Thompson (2008), we restrict the optimal weights to be in the [0, 1.5] range, which is technically similar to restricting the forecast to a (nonextreme) positive value.

27. The moving-block bootstrap is shown (see, e.g., Lahiri (1999)) to be comparable in performance to other widely used methods, for example, the stationary bootstrap by Politis and Romano (1994) and the circular block bootstrap of Politis and Romano (1992). However, constant block sizes lead to smaller mean-squared errors compared with random block sizes used in a stationary bootstrap. Technically, we draw 10,000 random samples of 200 blocks, with blocks of 12 observations (i.e., 1-year blocks), to preserve the autocorrelation in the data.
Figure 6: Traditional approach: Out-of-sample $R^2$. The figure shows the out-of-sample $R^2$ (defined in (10)) and its p-value for predictions based on the traditional approach with a short (3-year) estimation window. Panels A and B depict the results for implied correlation (IC) and its components: the dispersion of market betas (IDMB), idiosyncratic variance (IdIV), and market variance (IV). Panels C and D depict the results for risk premiums for correlation (CRP), market variance (VRP), and upside and downside semivariances ($\text{VRP}^u$ and $\text{VRP}^d$). p-values are computed from bootstrapped distributions, and the dotted lines represent 5% significance bounds. The $R^2$ axis is cut at the $-$45% level for better readability. Predictions are made at a monthly frequency from January 1996 to December 2017.

Figure 6 reports the out-of-sample $R^2$ for univariate predictions using the traditional predictability approach and a 3-year estimation window.\textsuperscript{28} Implied correlation delivers positive $R^2$s of 1.6%, 6.0%, and 10.1% for 1-, 3-, and 6-month horizons (which are significant at the 10% level for the first and at the 5% level for the two longer horizons). In contrast, the components of implied correlation show no significant predictive power (Panels A and B). Also, there is almost no predictability in the case of the risk premiums for correlation and (semi)variances (Panels C

\textsuperscript{28}Note, to avoid overfitting, we always rely on a single predictor; optimizations (for example, model selection, overfitting corrections, and so on) of the out-of-sample predictions are left to future research. Results from a simple model averaging the three correlation components (as a way to reduce overfitting following Rapach, Strauss, and Zhou 2009) show stronger predictability relative to a model with joint predictors; however, most out-of-sample $R^2$s are still negative.
and D), with the exception of the correlation risk premium at the 3-month horizon and the downside variance risk premium at the 6-month horizon.

Importantly from an economic perspective, implied correlation improves the portfolio performance relative to a naive prediction by 3%–4% p.a. in certainty equivalent terms (Panels A and B of Figure 7), outperforming all its components for long horizons. Within the set of risk premiums, the downside semivariance risk premium performs best with certainty-equivalent gains between 2.5% and 3.5% p.a., followed by the correlation risk premium for intermediate horizons (Panels C and D).
Intuitively, when choosing the estimation horizon for the rolling-window regressions (12), one typically faces a trade-off between the precision of the coefficients $\beta_{k,t}$ and their ability to reflect the current economic conditions. Variations in the estimation window show that traditional out-of-sample regression techniques cannot fully exploit the predictive power of many variables, because they require a relatively long historical estimation window for the regression coefficients. In addition, the traditional approach has another drawback; that is, to avoid any look-ahead bias, when forecasting returns from $t$ to $t + \tau_r$, the last observations of the predictors used in the estimation of the regression coefficients in (12) are from time $t - \tau_r$. Hence, for an annual forecasting horizon, this implies that the predictors and the estimated predictive relation will be 1 year old and, in the case of changing economic conditions, severely outdated.

### 4.3 Contemporaneous-Beta Approach

In light of these findings, we now propose a new approach for out-of-sample forecasts that relies on contemporaneous betas computed from higher-frequency data and significantly improves return predictability. The approach can be applied to state variables with observable risk premiums and, hence, is especially suited to option-implied variables.

#### 4.3.1 Intuition

The approach effectively extends the contemporaneous-regression idea, introduced by Cutler, Poterba, and Summers (1989) and Roll (1988). Their approach traditionally has been used to study contemporaneous innovations in market excess returns and the respective variables (similar to our VAR analysis in Section 3.2). In contrast, our objective is to combine the coefficients obtained from the contemporaneous regressions using forward-looking option-implied variables with time-$t$ forward-looking risk premiums to efficiently forecast future market excess returns.\(^\text{30}\)

Intuitively, the idea can be motivated by a simple linear framework within the arbitrage pricing theory. For example, consider a setting in which the market excess return is described

\(^{29}\) For a variety of rolling-window horizons ranging from 1 to 5 years, the results are qualitatively the same.

\(^{30}\) Pyun (2019) employs a similar idea, using shocks to expected daily variance under the physical probability measure to estimate contemporaneous-beta coefficients.
by a linear factor model with (time-varying) factor exposures:

\[ r_{t+1} = \sum_{k=1}^{K} \beta_{k,t} f_{k,t+1} + \epsilon_{t+1}, \]  
(13)

where \( f_{k,t+1} \) denotes the return on factor \( k \in \{1, \ldots, K\} \), and \( \epsilon_{t+1} \) denotes the “noise.” In this case, the equity risk premium is given by

\[ ERP(t, t+1) = \sum_{k=1}^{K} \beta_{k,t} RP_{k,t+1} + p_t(\epsilon_{t+1}), \]  
(14)

where \( RP_{k,t+1} \) denotes the risk-premium on the \( k \)th factor, and \( p_t(\epsilon_{t+1}) \) denotes the pricing error, for example, because of omitted factors. Essentially, to arrive at a good estimate for the future market excess return, one needs precise estimates of the time-\( t \) factor exposures \( \beta_{k,t} \) and the corresponding risk premiums \( RP_{k,t+1} \).

Our approach relies on first estimating a regression of the type (13) using daily (or even intraday) market excess returns and, at the same frequency, shocks to the (option-implied) variables, such as implied correlation or implied variance. Doing so delivers accurate and up-to-date estimates of \( \beta_{k,t} \). Intuitively, the higher frequency observations have two advantages: (1) they improve the properties of the regression coefficients (betas), which are essentially functions of second moments, and (2) they allow us to shorten the estimation window so that betas quickly adjust to new information. In the second step, one can then use the “pricing equation” (14) to predict future market excess returns by combining the estimated coefficients with the time-\( t \) forward-looking risk premiums on the respective variable (e.g., the correlation risk premium or the variance risk premium).

4.3.2 Implementation

For estimating regression (13), the contemporaneous-beta approach requires estimating shocks in the variables, that is, estimates of the “factors.” In the case of option-implied variables, these

\[ \text{A similar structure endogenously arises in Bollerslev, Tauchen, and Zhou (2009), Bollerslev, Todorov, and Xu (2015), Kilic and Shaliastovich (2017), and Feunou, Jahan-Parvar, and Okou (2017).} \]

\[ \text{Although early applications of the arbitrage pricing theory (e.g., Ross 1976) derived bounds on the pricing errors by assuming a correct specification of a linear factor model, recent studies (e.g., Raponi, Uppal, and Zaffaroni 2018) show that the errors are bounded even when the model is misspecified or factors are omitted.} \]
shocks can be proxied for using shocks to integrated expected variables. For example, note that the time-\(t\) expected integrated correlation obtained from options with maturity \(T\) can be decomposed as follows:

\[
IC(t, T) = E_t^Q \left[ E_{t+\Delta t}^Q \left[ \int_t^{t+\Delta t} \rho(s) ds + \int_{t+\Delta t}^T \rho(s) ds \right] \right]
\]

\[
= E_t^Q \left[ \int_t^{t+\Delta t} \rho(s) ds \right] + E_t^Q [IC(t + \Delta t, T)],
\]

where \(\rho\) denotes the stochastic process of correlation, and \(Q\) denotes the risk-neutral probability measure. Hence, increments of implied correlation are given by

\[
\Delta IC(t + \Delta t, T) = IC(t + \Delta t, T) - IC(t, T)
\]

\[
= IC(t + \Delta t, T) - E_t^Q [IC(t + \Delta t, T)] - E_t^Q \left[ \int_t^{t+\Delta t} \rho(s) ds \right].
\]  

(15)

If the last term in equation (15)—the expected integrated correlation over a short period of time \(\Delta t\)—is small, that is, if risk-neutral expected integrated correlation can be well approximated by a martingale,\(^{33}\) short-interval increments are indeed proxies for random shocks to correlation. The same argument holds for shocks to (semi)variances.

Importantly, our approach allows us to use increments from any option maturity; in particular, one can use variables extracted from the most liquid options at short maturities. Doing so reduces the potential bias in betas arising from nonlinearities in response to random shocks in a variable. One only needs to correct the resultant betas for the difference in variability of the regressors used for beta estimation (i.e., increments in variables) in (13) and the variability of the risk premiums for the pricing equation (14). Appendix B derives a simple procedure that does exactly that.

\(^{33}\)Empirical evidence supports this approximation. For example, Filipović, Gourier, and Mancini (2016, p. 58) find that a “martingale model provides relatively accurate forecasts for the one-day horizon variance.” Moreover, integrated expected variance and the integrated expected correlation are highly persistent, with first-order autocorrelations between 0.97 and 0.994 for variance and between 0.97 and 0.993 for correlation at various option maturities in our sample period.
4.3.3 Results

To illustrate the advantages of the contemporaneous-beta approach relative to the traditional approach, we now compare its performance for the case of a 3-year historical rolling-window estimation period. Recall that in this case, only implied correlation significantly predicted returns out-of-sample for the traditional approach, whereas there is no out-of-sample predictability for the risk premiums (cf. Figure 6).

To estimate the contemporaneous betas, we use daily market excess returns and daily increments in implied correlation and implied (semi)variances from options with 1-month maturity.\textsuperscript{34} For the out-of-sample predictions, we then combine these betas with the time-\textit{t} expected risk premium on the predictors, that is, the correlation and the (semi)variance risk premiums, for an option maturity matching the forecasting horizon.

As shown in Figure 8, despite the short estimation window, the new approach leads to a stable out-of-sample return predictability for most horizons. The correlation risk premium delivers the highest out-of-sample $R^2$ for 3- to 9-month horizons, whereas the downside semivariance risk premium performs best at the very short (1-month) horizon. Interestingly, even the variance risk premium displays a decent performance with an $R^2$ of 7% at a 1-month horizon, declining to 2.2% for 6 months. The $R^2$s for the correlation risk premium are significant for horizons up to 9 months, for the downside semivariance risk premium up to 6 months, and for the variance risk premium for 1 and 3 months.

Results shown in Figure 9 confirm that the market return predictions by the correlation risk premium based on the contemporaneous-beta approach indeed prove useful for a myopic mean-variance investor. The certainty-equivalent gain for the correlation risk premium is above 4% for horizons of 1 to 6 months and significant for up to 9 months. The downside semivariance risk premium is now slightly inferior to the correlation risk premium for short horizons and loses significance for longer ones. Overall, the gains in the risk-adjusted return are stronger with the contemporaneous-beta approach compared to the traditional one.\textsuperscript{35}

\textsuperscript{34}These are then adjusted by the ratio of the 3-year historical volatilities of the implied variables and the respective risk premiums, as described in Appendix B.

\textsuperscript{35}Notably, even for an extremely short estimation window of 1 month, the predictive performance is impressive (results are available on request).
To understand what drives the differences in the approaches’ predictive power, recall that the pricing equation is the same for the traditional and the contemporaneous-beta approaches. However, the two approaches considerably differ in the estimation of the regression coefficients, $\beta_{k,t}$. Figure 10 depicts the estimated betas for the various variables and forecasting horizons. Notably, the resultant betas show very different dynamics. That is, the traditional betas are far more volatile (pay attention to the $y$-axis scales) and exhibit more abrupt jumps in re-
action to “extreme” observations. Also, whereas the traditional betas often change sign, the contemporaneous betas, though substantially fluctuating over time, remain positive (consistent with theory). Moreover, the traditional betas fluctuate much more with the forecasting horizon, with standard deviations across horizons that are 5 to 25 times larger than those of the contemporaneous approach.

5 Robustness

In the following, we carry out a series of additional tests that confirm the robustness of our main findings for various alternative specifications. Appendix E houses figures and tables containing the detailed results of these exercises.

First, to remove potential biases in the $R^2$'s of the predictive regressions for the macroeconomic variables induced by overlapping observations, we repeat these predictive regressions with non-overlapping predictions. In particular, for a given forecasting horizon and predictor, we run regressions for each starting month and then compute the average $R^2$. Overall, the results are similar to those presented in Section 2, with an expected downward correction in $R^2$'s for longer horizons (see Figure RF1). The economic policy uncertainty indicator (BOI), for which only implied correlation delivers a positive $R^2$ for long horizons, is most affected.

Second, for similar reasons (overlapping observations), we also redo the in-sample market return predictive regressions using non-overlapping regressions (in the same way as we did for the macro-economic variables above). Also, we compute the univariate $R^2$'s adjusted for the autocorrelations of the predictors using the procedure outlined in Boudoukh, Richardson, and Whitelaw (2008). The $R^2$'s substantially decline in both cases; however, notably, implied correlation still delivers the strongest predictive power at longer horizons (Figures RF2 and Figure RF3, respectively). These findings are supported by additional tests based on the instrumental variable approach by Kostakis, Magdalinos, and Stamatogiannis (2015). In most cases, our initial corrections for autocorrelations based on Newey-West standard errors are stricter than those from the instrumental variable approach; hence, the results remain unchanged.

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36 In particular, as shown by Boudoukh, Richardson, and Whitelaw (2008), for highly persistent regressors, in-sample $R^2$'s mechanically increase with the predictability horizon in the case of overlapping observations.

37 We are grateful to the authors for providing the code on their website.
Figure 10: Dynamics of out-of-sample regression coefficients. This figure shows the time series of the regression coefficients for univariate models of out-of-sample market return forecasts at forecasting horizons of 1, 6, and 12 months. The panels on the left show the regression coefficients from the traditional approach, and the ones on the right show the regression coefficients from the contemporaneous approach. For both approaches, we use a 3-year historical estimation window.
Third, to ensure that our findings for in-sample market return predictability are robust to the addition of “traditional predictors,” we run regressions controlling for the Earnings Price Ratio ($EP$), the Term Spread ($TMS$), the Default Yield Spread ($DFY$), the Book-to-Market Ratio ($BTM$), and the Net Equity Expansion ($NTIS$).\(^{38}\) To avoid overfitting, we select, for each predictive horizon, the relevant variables by applying a LASSO procedure to regression (7), selecting the optimal regularization parameter using the Akaike information criterion (AIC). Overall, the predictive power of implied correlation and its components is not much affected by the additional controls. In particular, implied correlation is always selected by the LASSO procedure and remains highly statistically significant for longer horizons (Table RT1). Also, the components of implied correlation are practically always selected by the procedure, and their significance is unchanged.

Fourth, to analyze the sensitivity of the in-sample predictability results with respect to the sample period, we carry out a number of subsample analyses. This includes (1) conditioning on implied correlation being below and above its median (Panels A and B in Table RT2), (2) splitting the sample in two halves (Panels C and D), and (3) conditioning on NBER recession (Panels E and F). At short horizons, the predictive power of implied correlation is better when its value is low and vice versa for long horizons. Also, the predictive power is considerably better in the first half of the sample, and long-term predictability improves during recessions.

Fifth, we study out-of-sample return predictability using a long (10-year) estimation window for the traditional approach (Figure RF4).\(^{39}\) Although the out-of-sample $R^2$ for predictions based on implied correlation is initially negative, it demonstrates a steady increase from about 1\% for 3 months to about 14\% at the 9- and 12-month horizons, delivering the highest predictive power among the predictors at 6-month and longer horizons. For 1- and 3-month horizons, idiosyncratic variance performs the best with $R^2$s around 3\%–4\%. In the case of the risk premiums, hardly any variable delivers an $R^2$ that is statistically different from zero.

\(^{38}\)We construct the variables following Goyal and Welch (2008). That is, $EP$ is defined as the log ratio of earnings to prices; $TMS$ is the difference between the long term yield on government bonds and the Treasury bill; $DFY$ is the difference between BAA and AAA-rated corporate bond yields; $BTM$ is the ratio of book value to market value for the Dow Jones Industrial Average; and $NTIS$ is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks.

\(^{39}\)Here, we follow Kilic and Shaliastovich (2017), who use a 10-year window to show that decomposing the variance risk premium into good and bad components improves the out-of-sample predictability of market returns.
6 Conclusion

The correlation among individual stocks implied by option prices ("implied correlation") is one of the most robust predictors of long-term market excess returns. In this paper, we further explore its predictive power and, most importantly, study its underlying economic sources.

In particular, we show that implied correlation is a leading procyclical state variable, generally predicting future investment opportunities, that is, financial-market risks and macroeconomic conditions for 6 to 18 months ahead. We provide empirical evidence that implied correlation inherits this predictability from its three main components—implied market variance, implied idiosyncratic variance, and the implied dispersion of market betas—which, individually, also predict future investment opportunities. Indeed, linear combinations of its three main components usually outperform implied correlation in predicting future financial risk measures and macroeconomic variables, indicating that some information is lost when aggregated into the specific functional form of correlation.

We also provide additional (new) evidence of long-term market excess return predictability by implied correlation. First, we document that its three main components can also predict future market returns in-sample and, when used jointly, outperform implied correlation in terms of predictive power. Second, we document that the predictability by implied correlation is not subsumed by measures of tail risk, such as the variance, correlation or the downside semivariance risk premium. Third, the predictability is also robust to traditional return predictors. Fourth, we provide first empirical evidence of robust out-of-sample return predictability by implied correlation, leading to high out-of-sample $R^2$'s even at long horizons and substantial economic gains for market-timing strategies.

We also make a methodological contribution in proposing a novel extension of the contemporaneous-beta approach that overcomes the problem of the high sensitivity of the traditional approaches to the length of the estimation window and to anomalous observations (outliers) in the data. Our approach combines high-frequency increments in option-implied variables with their respective risk premium. We demonstrate that the approach can improve out-of-sample return forecasts in many applications because of its stable and up-to-date regression coefficients.
Moreover, because of its straightforward implementation, the contemporaneous-beta approach naturally lends itself to other settings.

By highlighting the importance of information not spanned by the marginal distribution of the market, our results have important implications for theoretical work building pricing models from individual stock dynamics (see, e.g., Leippold and Trojani (2010)). Moreover, by providing evidence of the pricing of idiosyncratic variance at the aggregate level, our work connects to the ongoing debate about the importance and pricing of idiosyncratic risk.
References


Appendix

A Option-Implied Beta Construction

To construct option-implied market betas, we follow the approach proposed by Buss and Vilkov (2012). In a first step, we compute an option-implied correlation matrix for all index components; based on the following parametric form for implied correlations $\rho_{Q_{i,i}}^t(t)$:

$$\rho_{Q_{i,i}}^t(t) = \rho_{P_{i,i}}^t(t) - \alpha(t)(1 - \rho_{P_{i,i}}^t(t)).$$  \hfill (A1)

Intuitively, this expression models the implied correlation, $\rho_{Q_{i,i}}^t(t)$, as the expected physical correlation, $\rho_{P_{i,i}}^t(t)$, plus a heterogeneous correlation risk premium which is driven by the correlation-risk-premium parameter $\alpha(t)$ and inversely proportional to the physical correlation.\textsuperscript{40} Importantly, this specification guarantees the positive-definiteness of the resultant correlation matrix.

Substituting the implied correlations (A1) into restriction (3), one arrives at the following expression for $\alpha(t)$:

$$\alpha_t = -\frac{(\sigma_{Q_i}^2(t))^2 - \sum_{i=1}^N \sum_{i' = 1}^N \omega_i \omega_{i'} \sigma_{Q_i}(t) \sigma_{Q_{i'}}(t) \rho_{P_{i,i'}}^t(t)}{\sum_{i=1}^N \sum_{i'=1}^N \omega_i \omega_{i'} \sigma_{Q_i}^2(t) \sigma_{Q_{i'}}^2(t)(1 - \rho_{P_{i,i'}}^t(t))}.$$

which, together with (A1), is used to construct the “full” implied correlation matrix $\Omega^Q(t) = \{\rho_{Q_{i,i}}^t(t)\}$.

Pre- and postmultiplying the correlation matrix $\Omega^Q(t)$ by a diagonal matrix of option-implied stock volatilities, one gets the option-implied variance-covariance matrix $\Sigma^Q(t)$. Finally, the vector of option-implied market betas can be obtained as

$$\beta^Q(t) = \frac{\Sigma^Q(t) \times W}{(\sigma_M^Q(t))^2},$$

where $W$ denotes the $N \times 1$ vector of index weights $\omega_i$ and $\sigma_M^Q(t)$ denotes the implied volatility of the market (index).

\textsuperscript{40}For the empirical implementation, we rely on a historical 1-year rolling-window correlation matrix for individual stocks, though the results are robust to variations in the window length.
B “Normalizing” Variance and Correlation Betas

The variance and correlation betas, $\beta_{\Delta IV,t}$ and $\beta_{\Delta IC,t}$ estimated by regressing market excess returns on increments in option-implied variables in (13), differ from the exposures $\beta_{V,t}$ and $\beta_{\rho,t}$ in the pricing equation (14). In particular, they need to be adjusted for the difference in the variability of the regressors used for beta estimation (i.e., increments in risk-neutral expected variance and correlation) and the variability of the predictors in the pricing equation (i.e., the variance and correlation risk premium).

Intuitively, the variance beta in the pricing equation, $\beta_{V,t}$, can be decomposed into (i) the correlation between the market excess return and the variance risk premium, and (ii) the ratio of their volatilities. Similarly, the variance beta in the estimation equation, $\beta_{\Delta IV,t}$, can be decomposed into (i) the correlation between the market excess return and the increments in implied variance, and (ii) the ratio of their volatilities.

Consequently, if we assume that the correlation between returns and increments in implied variance equals the correlation between returns and the variance risk premium, that is, $\text{Corr} (r_{t+\tau}, VRP(t, t + \tau)) = \text{Corr} (r_{t+\tau}, \Delta IV(t, t + \tau))$, one gets:

$$
\beta_{V,t} = \text{Corr} (r_{t+\tau}, VRP(t, t + \tau)) \times \frac{\text{Vol} (r_{t+\tau})}{\text{Vol} (VRP(t, t + \tau))} \\
= \text{Corr} (r_{t+\tau}, \Delta IV(t, t + \tau)) \times \frac{\text{Vol} (r_{t+\tau})}{\text{Vol} (\Delta IV(t, t + \tau))} \times \frac{\text{Vol} (\Delta IV(t, t + \tau))}{\text{Vol} (VRP(t, t + \tau))} \\
= \beta_{\Delta IV,t} \times \frac{\text{Vol} (\Delta IV(t, t + \tau))}{\text{Vol} (VRP(t, t + \tau))}.
$$

Accordingly, one can simply adjust the variance beta, $\beta_{\Delta IV,t}$, by the ratio of the volatility of the increments in implied variance and the volatility of the variance risk premium. Both variables are observable, so that the ratio can easily be estimated from the data. The same principle works for up and down semivariance betas, and for correlation betas. For example, computations for the correlation risk premium lead to a comparable adjustment:

$$
\beta_{\rho,t} = \beta_{\Delta IC,t} \times \frac{\text{Vol} (\Delta IC(t, t + \tau))}{\text{Vol} (CRP(t, t + \tau))}.
$$
C Additional Figures

**A: IC to Other Variables**

- **IC to IC**
- **IC to DIV**
- **IC to MKTRF**

**B: Variables to MKTRF**

- **MKTRF to IC**
- **MKTRF to DIV**
- **MKTRF to MKTRF**

**C: DIV to Other Variables**

- **DIV to IC**
- **DIV to DIV**
- **DIV to MKTRF**

**D: MKTRF to Other Variables**

- **MKTRF to IC**
- **MKTRF to DIV**
- **MKTRF to MKTRF**

**Figure A1: VAR specification 1: Impulse response functions.** The figure shows a set of selected impulse response functions for a VAR(1) specification of (8) featuring the market excess return (MKTRF), the log dividend-growth (DIV), and the implied correlation (IC); for horizons of 1 to 12 months. The sample period spans from January 1996 to December 2017. The dotted lines indicate 5% confidence bounds.
Figure A2: VAR specification 5: Impulse response functions. The figure shows a set of selected impulse response functions for a VAR(1) specification of (8) featuring the market excess return (MKTRF), the log dividend-growth (DIV), the implied dispersion of market betas (IDMB), idiosyncratic variance (IdIV), and market variance (IV); for horizons of 1 to 12 months. The sample period spans from January 1996 to December 2017. The dotted lines indicate 5% confidence bounds.
D Additional Tables

Table A1: Autocorrelations. The table reports autocorrelations for option-based variables, computed from monthly observations, for maturities from 1 to 12 months. The variables include implied correlation (IC), implied variance (IV), and the risk premiums for correlation (CRP), variance (VRP) and upside and downside semivariances (VRP\textsuperscript{u} and VRP\textsuperscript{d}). The sample period spans from January 1996 to December 2017.

<table>
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<th>3</th>
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<tbody>
<tr>
<td>IC</td>
<td>0.766</td>
<td>0.832</td>
<td>0.892</td>
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</tr>
<tr>
<td>IDMB</td>
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<td>0.934</td>
<td>0.940</td>
<td>0.946</td>
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<td>0.965</td>
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<tr>
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<td>0.906</td>
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<tr>
<td>CRP</td>
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<td>0.648</td>
<td>0.835</td>
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<td>VRP</td>
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<tr>
<td>VRP\textsuperscript{u}</td>
<td>0.480</td>
<td>0.792</td>
<td>0.924</td>
<td>0.948</td>
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<tr>
<td>VRP\textsuperscript{d}</td>
<td>0.266</td>
<td>0.444</td>
<td>0.678</td>
<td>0.753</td>
<td>0.802</td>
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Table A2: Time-series correlations. This table reports time-series correlations between option-based variables. Panel A shows correlations in levels and Panel B in the first differences. The variables include implied correlation (IC), implied variance (IV), and the risk premiums for correlation (CRP), variance (VRP) and upside and downside semivariances (VRP\textsuperscript{u} and VRP\textsuperscript{d}). All variables are computed from one-month options and are sampled daily.

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>IC</td>
<td>1.000</td>
<td>-0.521</td>
<td>-0.162</td>
<td>0.579</td>
<td>0.253</td>
</tr>
<tr>
<td>IDMB</td>
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<td>1.000</td>
<td>0.343</td>
<td>-0.099</td>
<td>-0.494</td>
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<td>0.343</td>
<td>1.000</td>
<td>0.602</td>
<td>-0.216</td>
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<tr>
<td>IV</td>
<td>0.579</td>
<td>-0.099</td>
<td>0.602</td>
<td>1.000</td>
<td>-0.013</td>
</tr>
<tr>
<td>CRP</td>
<td>0.253</td>
<td>-0.494</td>
<td>-0.216</td>
<td>-0.013</td>
<td>1.000</td>
</tr>
<tr>
<td>VRP</td>
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<td>-0.337</td>
<td>-0.377</td>
<td>0.362</td>
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<tr>
<td>VRP\textsuperscript{u}</td>
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<td>-0.042</td>
<td>-0.396</td>
<td>-0.551</td>
<td>0.308</td>
</tr>
<tr>
<td>VRP\textsuperscript{d}</td>
<td>0.333</td>
<td>-0.178</td>
<td>-0.125</td>
<td>0.130</td>
<td>0.408</td>
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Table A3: Risk premiums: Summary statistics. The table reports summary statistics (mean, standard deviation, and skewness) for the risk premiums on correlation (CRP), variance (VRP), and upside and downside semivariances (VRP\textsuperscript{u} and VRP\textsuperscript{d}). Statistics are annualized and reported for maturities of 1 to 12 months over a sample period from January 1996 to December 2017.

<table>
<thead>
<tr>
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<th>3</th>
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</tr>
</thead>
<tbody>
<tr>
<td>CRP</td>
<td>0.059</td>
<td>0.106</td>
<td>-0.170</td>
<td>0.099</td>
<td>0.083</td>
</tr>
<tr>
<td>VRP</td>
<td>0.006</td>
<td>0.028</td>
<td>-7.706</td>
<td>0.006</td>
<td>0.027</td>
</tr>
<tr>
<td>VRP\textsuperscript{u}</td>
<td>-0.001</td>
<td>0.017</td>
<td>-8.265</td>
<td>-0.001</td>
<td>0.016</td>
</tr>
<tr>
<td>VRP\textsuperscript{d}</td>
<td>0.009</td>
<td>0.013</td>
<td>-0.653</td>
<td>0.011</td>
<td>0.013</td>
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</table>
E  Robustness

Figure RF1: Economic condition predictions: Non-overlapping predictions. This figure reports the average $R^2$ of predictive regressions of future (log)changes in macro-economic variables on current option-implied variables for horizons of 1 to 12 months; sampled at a frequency equal to the predictive horizon (i.e., non-overlapping). The sample period spans from January 1996 to December 2017.
Figure RF2: In-sample return predictability: Non-overlapping predictions. The figure depicts the results of the in-sample market excess return predictability regressions (7) for horizons of 1 to 12 months; sampled at the frequency equal to the predictive horizon (i.e., non-overlapping). Panels A and B report the adjusted $R^2$ and $t$-statistics for regressions with implied correlation and/or its components as explanatory variables, respectively. Panels C and D report the adjusted $R^2$ and $t$-statistics for regressions with risk premiums for correlation (CRP), market variance (VRP) and upside and downside semivariances (VRPu and VRPd) as explanatory variables, respectively. Panels E and F report the adjusted $R^2$ and $t$-statistics for multivariate regressions, respectively. The sample period spans from January 1996 to December 2017, and the data are sampled monthly. Standard errors are corrected for autocorrelation following Newey and West (1987) and the black dotted lines indicate 5% significance bounds.
Figure RF3: In-sample return predictability: $R^2$ Adjustment. The figure depicts the $R^2$ of the in-sample market excess return predictability regressions (7) adjusted for autocorrelation following Boudoukh, Richardson, and Whitelaw (2008); for horizons of 1 to 12 months. Panel A shows the $R^2$ for univariate regressions with implied correlation ($IC$), the dispersion of market betas ($IDMB$), idiosyncratic variance ($IdIV$), and market variance ($IV$) as explanatory variables. Panel B reports the $R^2$ for univariate regressions with risk premiums for correlation ($CRP$), market variance ($VRP$) and upside and downside semivariances ($VRP^u$ and $VRP^d$). The sample period spans from January 1996 to December 2017.

Table RT1: In-sample return predictability: Traditional predictors. The table reports the results of the in-sample market excess return predictability regressions (7); for horizons from 1 to 12 months. Panels A and B show the results for regressions using implied correlation ($IC$) and its three components as (potential) explanatory variables, respectively. The regressions include a variety of “traditional” predictors; selected, for each predictive horizon, by applying a LASSO procedure to regression (7) (with an optimal regularization parameter based on the Akaike information criterion). ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively, based on Newey and West (1987) standard errors.
<table>
<thead>
<tr>
<th>Panel A: IC below median</th>
<th>Panel B: IC above median</th>
<th>Panel C: First Half of the Sample</th>
<th>Panel D: Second Half of the Sample</th>
<th>Panel E: Recession Indicator = 0</th>
<th>Panel F: Recession Indicator = 1</th>
</tr>
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<td>9 months</td>
<td>12 months</td>
<td>1 month</td>
</tr>
<tr>
<td><strong>Panel A: IC below median</strong></td>
<td><strong>Panel B: IC above median</strong></td>
<td><strong>Panel C: First Half of the Sample</strong></td>
<td><strong>Panel D: Second Half of the Sample</strong></td>
<td><strong>Panel E: Recession Indicator = 0</strong></td>
<td><strong>Panel F: Recession Indicator = 1</strong></td>
</tr>
<tr>
<td>IC</td>
<td>0.022</td>
<td>0.197</td>
<td>0.543***</td>
<td>0.984***</td>
<td>1.265***</td>
</tr>
<tr>
<td>IDM</td>
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<td>-0.308***</td>
<td>-0.668***</td>
<td>-0.806***</td>
<td>-0.872*</td>
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<tr>
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<tr>
<td>IV</td>
<td>-0.020</td>
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<td>2.35</td>
<td>23.71</td>
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**Table RT2: In-sample return predictability: Subsamples.** The table reports the results of the in-sample market excess return predictability regressions (7), for horizons from 1 to 12 months. Panels A and B condition on implied correlation being below and above its median value (for the whole sample), Panels C and D split the sample in two halves, and Panels E and F condition on the NBER recession indicator. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively, based on Newey and West (1987) standard errors. The sample period spans from January 1996 to December 2017.
Figure RF4: Traditional approach: Out-of-sample $R^2$. The figure shows the out-of-sample $R^2$ (as defined in (10)) and its p-value for predictions based on the traditional approach with a long (10-year) estimation window. Panels A and B depict the results for implied correlation ($IC$) and its components: the dispersion of market betas ($IDMB$), idiosyncratic variance ($IdIV$), and market variance ($IV$). Panels C and D depict the results for risk premiums for correlation ($CRP$), market variance ($VRP$) and upside and downside semivariances ($VRP^u$ and $VRP^d$). p-values are computed from bootstrapped distributions and the dotted lines indicate 5% significance bounds. Predictions are made at a monthly frequency from January 1996 to December 2017.